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published in
IEEE Transactions on Biomedical Engineering
2007

DOI (link to publisher)
10.1109/TBME.2006.889202

Communications

Independent Component Analysis of High-Density Electromyography in Muscle Force Estimation

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***Abstract*—Accurate force prediction from surface electromyography (EMG) forms an important methodological challenge in biomechanics and kinesiology. In a previous study (Staudenmann *et al.*, 2006), we illustrated force estimates based on analyses lent from multivariate statistics. In particular, we showed the advantages of principal component analysis (PCA) on monopolar high-density EMG (HD-EMG) over conventional electrode configurations. In the present study, we further improve force estimates by exploiting the correlation structure of the HD-EMG via independent component analysis (ICA). HD-EMG from the triceps brachii muscle and the extension force of the elbow were measured in 11 subjects. The root mean square difference (RMSD) and correlation coefficients between predicted and measured force were determined. Relative to using the monopolar EMG data, PCA yielded a 40% reduction in RMSD. ICA yielded a significant further reduction of up to 13% RMSD. Since ICA improved the PCA-based estimates, the independent structure of EMG signals appears to contain relevant additional information for the prediction of muscle force from surface HD-EMG.**

***Index Terms*—Force estimation, human, independency, principal component analysis, redundancy, surface electromyography, variability.**

I. Introduction

The accuracy of muscle force prediction based on surface electromyography (EMG) forms an important methodological challenge in biomechanics and kinesiology. In general, surface EMG signals represent a summation of motor unit (MU)-potentials. Since MU-potentials are bi-phasic and appear after randomly distributed intervals [2], constructive and destructive superpositions may occur [3] causing a large variance of the EMG's linear envelope [4], [5]. Consequently, estimations of muscle activation and force from such linear envelopes have limited reliability. Model studies showed that summing MU-potentials after rectification can reduce the variability of the linear envelope [4]–[7]. Extracting independent information from a set of surface EMG signals might be used to obtain most of the separate MU-potentials. Along this line, we have already shown that using principal component analysis (PCA) for the removal of common information from a set of signals collected with a high-density EMG (HD-EMG) grid [8], [9] can improve EMG-based muscle force estimation [1].

Manuscript received April 24, 2006; revised September 24, 2006. *Asterisk indicates corresponding author.*

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Digital Object Identifier 10.1109/TBME.2006.889202

Surface EMG is always contaminated by common sources (volume conduction), at least to some degree. Volume conduction may cause (trivial) spurious correlations which can, in all generality, only be avoided by measuring all individual MUs. Obviously, this appears not feasible and, whenever possible, noninvasive surface recordings are to be preferred over intramuscular needle EMG. By construction, mode decomposition via PCA cannot solve this problem completely, because the modes extracted are not necessarily independent [10]. Therefore, we attempted to eliminate spurious correlations via independent component analysis (ICA) as a method for a so-called blind source separation [10]. ICA has been proven effective in extracting information on single MUs from multichannel EMG [11], [12].

Hence, with the present study we aimed for investigating whether using ICA may yield further improvements of muscle force estimation from (already PCA-reduced) HD-EMG signals.

II. Methods

A. Measurement

Details of the methods have been described previously [1], [7]. Briefly, eleven healthy subjects (age 28.0 ± 4.1 years, weight 67.6 ± 9.4 kg, and length 1.8 ± 0.1 m) performed isometric extensions at two arm elbow angles (60°, 130°) and at three levels of maximum voluntary contraction (20%, 50%, and 80%MVC). Subjects were instructed to avoid co-contraction (e.g., activity of biceps brachii muscle). The efforts had a rectangular pattern, consisting of a two-state isotonic contraction, starting at rest, followed by a plateau of 5 s and returning to rest. Surface EMG was measured using an active HD-EMG grid (BIOSEMI, Amsterdam, NL) [8] over the triceps brachii muscle. Force was measured using a strain gauge transducer (FUTEK L2353, ADVANCED SENSOR TECHNOLOGY, Irvine, CA). The HD-EMG grid consisted of 13×10 electrodes (5-mm interelectrode distance). Signals were collected monopolarly, band-pass filtered (band 0.16–500 Hz) and sampled at 2048 samples/s (16-bit analog-to-digital converter, $1\ \mu\mathrm{V/bit}$).

B. Analysis

Analysis was preformed in MATLAB 6.5 (The Mathworks, Inc, Natick MA) according to the following steps: 1) high-pass filtering the monopolar EMG-signals (MON); 2) mode reduction via PCA and (subsequently) ICA; 3) full-wave rectification and summing; 4) compensation for electro-mechanical delay via cross-correlating force and EMG; 5) low-pass filtering; 6) normalization to the average over the plateau. Complete rectangular-shaped time series and the isotonic time series (plateau) were analyzed separately. For the complete time series, step (5) was realized using a bi-directional first-order Butterworth filter (cutoff 10 Hz) and for the plateau time series a second-order Savitzky-Golay polynomial filter (window size: 1501) was used. To measure the quality of force estimation, root mean square differences (RMSD) and correlation coefficients between force and normalized EMG signals were computed.

Our application of PCA has been described in a previous study [1]. In fact, PCA also served as preprocessing for ICA to discard irrelevant (co-variance) structures. First, we discarded the first PCA-modes (with eigenvalues larger than of $1.5 \cdot 10^{-3}$), since these mainly contained common information that has been shown irrelevant for muscle force estimation [1]. Second, ranked (descending eigenvalues)

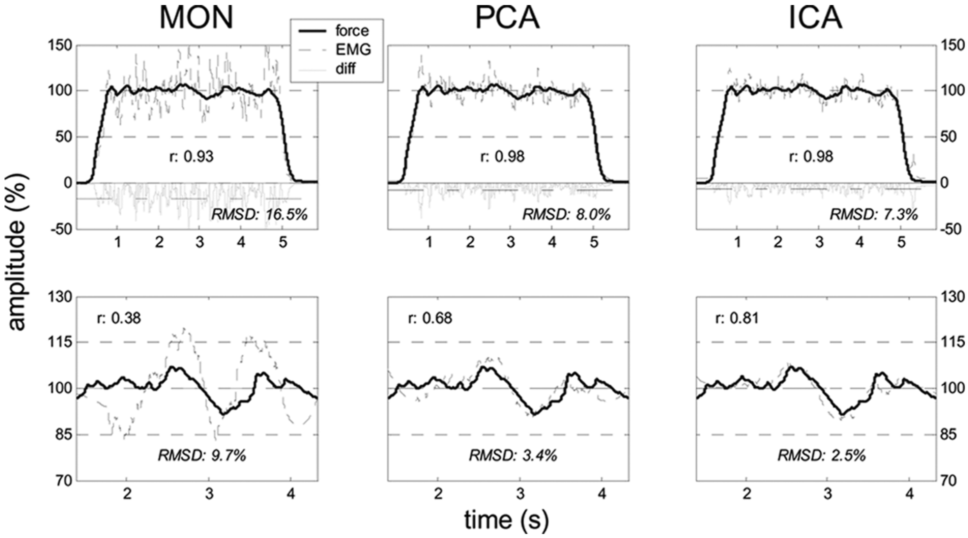

Fig. 1. Data of a representative trial (50%MVC) showing force and estimated force signals and minus the absolute difference between these (diff), and indicators of the quality of muscle force estimation (RMSD, correlation) for three different analysis methods (MON, PCA, ICA). The upper row shows the quality over the entire (rectangular) time series, the second row over the plateau time series. Note the improvement of force estimation quality for PCA and ICA not only over the entire rectangular force pattern but also within the fluctuations of the isotonic contraction.

PCA-modes showed a decrease in amplitude modulation for higher modes, primarily revealing the increasing presence of measurement noise. Although under normal circumstance these low-power modes would barely affect the subsequent analyses, the normalization applied here would potentially enlarge their (random) contribution to ICA-modes. Hence we discarded all PCA-modes of which the range of the normalized linear envelope was below 0.9. In sum, PCA was, thus, used as a "band-pass" filter prior to ICA.

Input signals into ICA (complete time series) were tested for kurtosis as, by definition, Gaussian input distributions of ICA yield modes that are identical to PCA modes—see, e.g., Hyvarinen *et al.* [10] for an excellent discussion of ICA. Here, we applied a fast fixed-point algorithm (FastICA 2.4) [13], [14] that was tested for robustness using different accuracy thresholds ($\varepsilon = 10^{-3}$ or $\varepsilon = 10^{-10}$) and different initial values (PCA-modes and random signals). Note that, for the sake of brevity, we only used FastICA but future studies should certainly test this choice against alternative algorithmic implementations of ICA.

C. Statistics

Statistical analysis was conducted in SPSS 12.0 (SPSS Inc., Chicago IL). A repeated measure analysis of variance (ANOVA) (Huynh-Feldt) was used with three fixed factors: "analysis method" (PCA versus ICA), "contraction level" (20%, 50%, and 80%MVC), and "elbow angle" (60°, 130°). Dependent variables were RMSD and correlation coefficient, the latter after correction with the Fisher Z-transform [15]. The significance level was 5%.

III. RESULTS

As expected, PCA of monopolar EMG-signals yielded a substantial improvement of muscle force estimation (40% RMSD), compared to solely using the monopolar signals. Interestingly, ICA yielded a further improvement in the quality of muscle force estimation, not only over the entire time series (5% RMSD), but also within the small force fluctuations of the plateau region (13% RMSD) (Fig. 1). The significant differences of RMSD and correlation coefficients between PCA and ICA are summarized in Fig. 2 and Table I. These differences can be understood because the kurtosis of the input-signals into the ICA ranged from 0.6–7.8 (with zero referring to a Gaussian distribution)

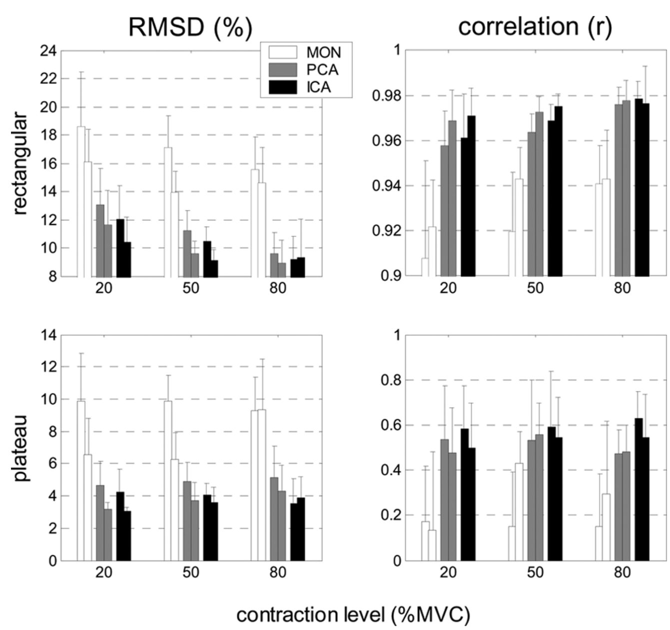

Fig. 2. Quality of muscle force estimation (RMSD, correlation) based on the three analysis methods (MON, PCA, and ICA) at two elbow angles (60° and 130° are left and right bars, respectively) and three contraction levels (20%, 50%, and 80% MVC). Left panels show RMSD over the entire rectangular and the plateau time series (upper, lower, respectively). Right panels show coefficients of correlation also over both time series. Bars represent average values over subjects, error bars represent standard deviations. Note that the scaling of the axes was altered to improve illustration.

their distribution was sharper than Gaussian. Therefore, ICA allowed for a further reduction of dependency between signals.

The amplitude modulation of the PCA-modes decreased for increasing modes (Fig. 3). Re-analysis of a typical trial without removal of the modes that showed an amplitude modulation of less than 0.9 resulted in an increase of the RMSD from 7.3% to 14.0%. Accuracy thresholds ($\varepsilon = 10^{-3}$ or $\varepsilon = 10^{-10}$) and initial guesses (PCA-modes and random signals) had no effect on RMSD and correlation, for both

TABLE I
RESULTS OF THE ANOVA ON RMSD AND z-TRANSFORMED COEFFICIENTS OF CORRELATION, WITH ANALYSIS METHOD (METHOD: PCA, ICA), CONTRACTION LEVEL (20%, 50%, AND 80%MVC), AND ELBOW ANGLE (ANGLE: 45°, 130°) AS INDEPENDENT VARIABLES. SIGNIFICANT VALUES HAVE BEEN PRINTED IN BOLD. NOTE THE HIGHLY SIGNIFICANT p-VALUES FOR THE MAIN EFFECT OF THE ANALYSIS METHOD

		entire rectangular pattern		plateau region	
		RMSD	correlation	RMSD	correlation
main	method	**0.003**	**0.001**	**0.002**	**0.011**
	%MVC	**0.016**	**0.020**	0.339	0.557
	angle	**0.011**	0.082	0.061	0.421
interaction	%MVC*meth	0.105	0.516	0.070	**0.017**
	angle*meth	0.630	0.325	**0.006**	**0.019**
	%MVC*angle	0.415	0.421	0.680	0.990
	%MVC*angle*meth	0.310	0.727	0.233	0.578

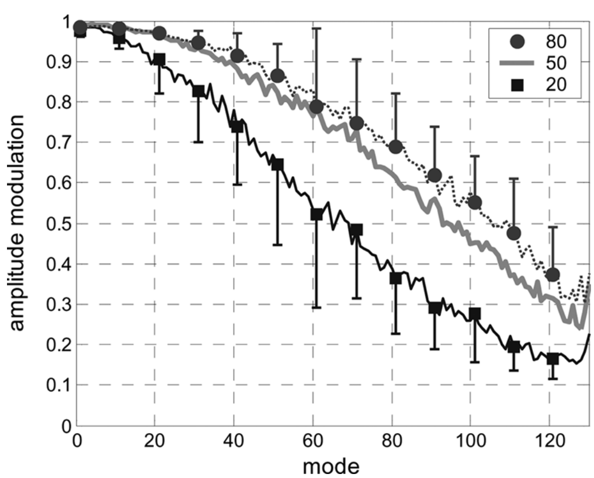

Fig. 3. Amplitude modulation of the ranked PCA-projections (descending eigenvalue) for three contraction levels (20%, 50%, and 80% MVC). Markers indicate mean values and error bars the standard deviations. Note the decreasing amplitude modulation for higher PCA-modes and the stronger decrease in amplitude modulation at lower contraction levels.

the entire rectangular-shaped pattern and the plateau region. Note, however, that the number of iterations was strongly affected showing besides the dependency on accuracy (ε) that the final ICA modes were 'close' to PCA modes (a typical data set, FastICA with $\varepsilon = 10^{-3}$ used 61 and 133 steps for preselected PCA-modes versus random signals, respectively; changing to $\varepsilon = 10^{-10}$, however, yielded 1000 steps before convergence).

IV. DISCUSSION

HD-EMG can generally provide substantial improvements in muscle force estimation [7], especially when supported by PCA as an extraction method [1]. That method requires no assumptions with respect to underlying sources, such as the muscle fiber architecture, that are, in principle, difficult to access. In the present study, we showed that further improvement in muscle force estimation from HD-EMG can be obtained by exploiting independent information by means of ICA from a subset of the principal components.

A. Independent Component Analysis

ICA yields improvements above PCA when signals do not display a Gaussian distribution (i.e., when the kurtosis is nonzero). The HD-EMG signals had a positive kurtosis indicating their so-called super-Gaussian character. Because independent components cannot be ranked like principal components [10], ICA does not allow for a direct reduction of dimensionality. Therefore, we used PCA as a preprocessing step eliminating undesired parts of the data (i.e., common information and modes strongly affected by noise).

In general, ICA is computationally less efficient than PCA because an explicit optimization is required to extract the independent components. Since changes in accuracy demands (ε) did not have significant effects on the quality of force estimation, the amount of iterations (particularly affected by that parameter) can be limited without major consequences for force estimation quality. In addition, the absence of effects of the initial guess (apart from a minor effect on the number of iterations) confirmed the robustness of the extracted independent components.

B. Physiological Relevance of ICA in Muscle Force Estimation

Active MUs are contributing to both EMG and muscle force so that more sophisticated extraction techniques applied to surface EMG potentially improve the estimation of muscle force. Our results support the idea that ICA succeeds to extract the underlying information from the signal set better than PCA alone. From a neurophysiological perspective, several arguments support that the extraction of independent information should, in principle, result in an improvement of the quality of EMG-based muscle force estimation.

As mentioned in the Introduction, extracting the maximal amount of independent information from the multiple sources (MUs) contributing to the EMG and rectifying the resulting signals before summation may reduce effects of (random) constructive and destructive superpositions. Further, MU activation may vary according to the location within the muscle. First, it has been suggested that small MUs tend to be located mainly in deeper parts within a muscle [16]–[20]. According to Henneman [21] at low contraction levels, these small MUs will be activated first. Evidence for such a deep to superficial order of recruitment has been found in EMG studies [19], [22]. Second, task-dependent variations in activation of MUs or muscle parts have been reported [19], [20], [23]–[27]. Consequently, the contribution of different MUs to the force produced may vary over time. To get a reliable estimate of the total force produced, therefore, the contributions of independently activated groups of MUs is necessary. Volume conduction [28]–[32] could mask such independent contributions of MUs especially in the monopolar signals used here, as these have been shown to contain much common information [7]. As shown previously, PCA is an efficient method to remove common information that proved irrelevant in muscle force estimation [1]. The present results indicate that an extraction, beyond the extraction-abilities of PCA, further improves signal extraction quality.

C. Limitation and Outlook

Force predictions, as performed in the present study, assume the absence of any co-contraction. Subjects were, therefore, instructed to relax the antagonist muscles. In addition, we tried to avoid co-contraction by measuring at "extreme" elbow angles (45°, 130°) only, where the antagonists (e.g., biceps brachii) have a substantially reduced force production capacity given their unfavorable location on the force-length relationship [33].

When applying ICA to extract independent information from multiple EMG signals, redundant but delayed information may be present in the signal(s) due to propagating MU action potentials. In general, such lags can strongly hamper extraction, since both covariance and correlation measures are rather sensitive towards phase delays [34], [35]. Future methods need to address this problem in more detail (e.g., [36]), although, in view of the present and our previous results, further improvements of the quality of muscle force estimations are expected to be quite modest.

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